CRPASE
Computational Research Progress in Applied Science & Engineering
ISSN 2423-4591
CRPASE Vol. 05(02), 52-57, June 2019

A New Method for Dental Caries Diagnosis Using Convolutional Neural Networks and Bees Algorithm

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Keywords

Dental caries,
Diagnosis,
Convolutional neural networks,
Bee's algorithm,
X-ray images.

Abstract

Over the past few years, dental radiography has played an important role in clinical diagnosis, treatment and surgery. Accordingly, extensive efforts have been done on improving computerized dental X-ray image analysis systems for clinical usages. This paper proposes a new method based on convolutional neural networks (CNNs) and bee's algorithm (BA) for detection and diagnosis of dental caries on X-ray image. The proposed method includes two main modules: classifier module and optimization module. In the classifier module, the CNN is used as the main classifier. One of the advantages of CNN is feature representation that is learned automatically from the training data, which is a critical difference from conventional hand-crafted feature representations. On the other hand, there are many parameters and hyper-parameters that affect the network's performance significantly. However there are not any systematic way to select the optimal value of these parameters and hyper-parameters. Therefore in the optimization module of the proposed method, we used BA to find the optimal architecture of the CNN. The proposed method was evaluated on a set of X-ray images collected in Shahid Beheshti University and the obtained results showed the excellent performance of proposed method.

1. Introduction

Chronic diseases are the main problems in public health worldwide. The pattern of disease has been transformed and oral diseases are considered one of the main public health problems due to its high incidence and prevalence in all regions of the world, and, as in all diseases, the greatest burden is on populations disadvantaged and socially marginalized; treatment of the conditions is extremely expensive and is not feasible in most low and middle income countries. This characteristic represents an important problem, since, according to the World Health Organization (WHO), oral diseases are the fourth most expensive cause to treat in the most industrialized countries [1]. Caries is the most frequent condition and according to the WHO; it affects between 60% and 90% of children of school age between 5 to 17 years old [2, 3].

Although dental caries is readily accessible for visual inspection, compared to approximal surfaces, their visual-tactile or radio graphical diagnosis is a difficult task due to the complicated three-dimensional shape of the occlusal surfaces, leading to a wide range of individual diagnostic decisions. The diagnosis of dental caries consists of the detection of the lesion followed by its assessment and classification, in terms of the stage of progress and its activity (whether a lesion is active and continues to progress or is arrested and the progress has stopped). Visual or visual-tactile inspection is a common conventional method for caries detection and classification in the daily clinical practice. However, this assessment is very subjective, since it is primarily based on the experience of the clinician, as well as, to factors related to illumination of the tooth, presence of dental plaque, stains, etc. This diagnostic variability between clinicians leads to different decisions for the management of the carious lesions and several of them might be to the wrong direction [4, 5].

In an attempt to reduce the variability in clinical diagnosis and improve its accuracy, several techniques have been developed for the detection and assessment of occlusal caries. These include fiber optic transillumination, laser or light or infrared fluorescence, electrical resistance [6] and more recently digital radiography, infrared thermography, optical coherence tomography (OCT), tera-hertz imaging and digital photography analysis [7, 8]. The current procedure assumes that the image is recorded on an X‑ray film and that it is interpreted by a human expert. Obviously,

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Received: 5 April 2019; Accepted: 25 May 2019

this suffers from the human error and error with visual inspection, which may further be enhanced by poor quality of the images. Many investigators believe that automation of dental caries screening analysis increases the rate of early detection and diagnosis accuracy. In recent years, machine learning algorithms have been successfully applied on medial signals and images [9- 11]. Regarding dental caries, several methods based on artificial neural networks, support vector machine and fuzzy systems have been proposed for dental caries diagnosis [12- 14].

A class of machine learning techniques named deep learning was developed mainly since 2006, where many layers of non-linear information processing stages or hierarchical architectures are exploited. Deep learning performance is better than the existing classification methods. In the conventional machine learning methods such as multi-layer Perceptron neural network (MLPNN), fuzzy systems and support vector machine (SVM) it is needed to extract the effective features manually [16- 22]. In this context, the convolutional neural networks (CNN) is able to learn the feature vector directly from the training data without any hand-crafting to determine the feature vector [23].

Based on the published papers about the automatic dental caries diagnosis, there are some facts which should be considered during the design of recognizer. One of these issues is the feature extraction. In recent years, many statistical and shape features have been introduced by researchers. Another issue is related to the choice of the classification approach to be adopted. In this paper, we employed CNN combination to automatically diagnosis the dental caries. Unlike the conventional analysis methods so far followed, the proposed system does not require any feature extraction.

The rest of the paper is organized as follows. Section 2 presents the basic concepts including CNN and BA. Section 3 presents the proposed method. Section 4 shows some simulation results and finally section 5 concludes the paper.

2. Basic Concepts

In this work, an intelligent method is proposed for detection and diagnosis of dental caries on X-ray image. In the proposed method we used combination of CNN and BA. In this section these concepts are described briefly.

2.1. CNN

CNNs are special type of MLP. They are similar to neural networks in the following aspects. They are made up of neurons with weights and biases which have to be learned. Some inputs are given to each neuron. Then, an operation of dot product is performed followed by an optional function of nonlinearity. CNN is buildup of basically three types of main layers. They are Convolutional layer, Pooling layer and a fully connected layer with a rectified linear activation function (ReLU) [23]. The main structure of CNN is shown in Figure 1. The CNN network can be expanded by adding more convolution and pooling layers. In this figure, CNN has two convolution and pooling layers.

The convolution layer performs feature extraction, and it is usually interspersed with sub-sampling layers to reduce the computation cost. Each layer contains multiple neurons and each of them has their own weights. Feature extraction can be achieved by multiple roll over convolution layers and pooling layers. This is the most important part of the convolutional neural network, and the classification is achieved by the last layer. The convolution layer has a local receptive structure, which is achieved by using a sparse connection, where a neuron with only one part of the input is connected. The sub pooling layer reduces the training difficulty. Furthermore, for each convolution layer neuron, their connection weight is the same, so the computation cost can be significantly reduced. In the convolutional neural network, the pooling layer usually follows the roll accumulation layer, and the pooling layer and the convolution layer may alternately appear many times, thus forming a multi-layer convolutional neural network.

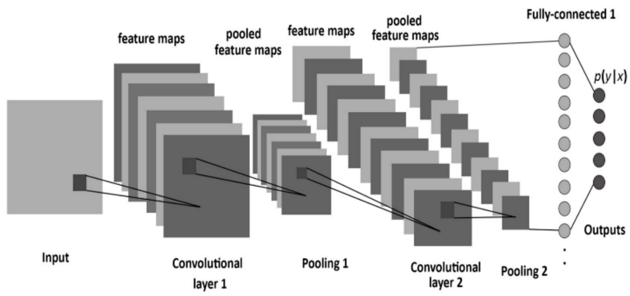

Figure 1. CNN structure [23]

CNNs were initially used in the area of image processing where it receives raw image pixels on the input end, transform it through a series of hidden layers and finally give the class scores at the other end. Our application is on analyzing signals which are one dimensional, so we use Convolution 1D layers, pooling 1D layers and fully connected layer. Here CNN takes the time series data in one dimensional form where in the data are arranged in the order of sequential time instants. In our case, the input one dimensional data vector is $x = (x_1, x_2, \dots, x_n)$ where $x_n \in R^d$ denotes features (here time series CCP data). Convolution 1D constructs a feature map fm by applying the convolution operation on the input data with a filter $w \in R^{fd}$ where f denotes the features inherent in the input data producing at its output, new set of features which is fed to input of the next block in line. A new feature map fm is obtained from a set of features f using Eq. (1)

$$hl_i^{fm} = tan\left(w^{fm} x_{i:i+f-1} + b\right) \quad (1)$$

The filter hl is employed to each set of features f in the input data defined by $\{x_{1:f}, x_{2:f+1}, \dots, x_{n-f+1}\}$ so as to generate a feature map as $hl = [hl_1, hl_2, \dots, hl_{n-f+1}]$ where $b \in R$ denotes a bias term and $hl \in R^{n-f+1}$.

The output of the convolutional layer is given to the pooling (POOL) layer. Convolutional layer uses ReLU activation function that apply $\max(0, \mathrm{x})$ to each of the inputs to the ReLU represented by x. The next layer (POOL) performs a down sampling operation. Here, the max-pooling operation is applied on each feature map $\overrightarrow{hl} = max\{hl\}$. This produces the most significant features. These selected features are fed to fully connected layer, containing the

Softmax function that gives the probability distribution over each class. Thus, the fully connected layer (FC) will compute the classes which form the final output of the CNN network. Thus the CNN has the architecture of INPUT-CONV-POOL-FC. In summary:

A CNN architecture is in the simplest case a list of Layers that transform the input volume into an output volume (e.g. holding the class scores)

There are a few distinct types of Layers (e.g. CONV/POOL/FC are by far the most popular)

Each Layer accepts an input volume and transforms it to an output volume through a differentiable function

Each Layer may or may not have parameters (e.g. CONV/FC do, POOL don't)

Each Layer may or may not have additional hyperparameters.

2.2. Bee's Algorithm

The bees algorithm (BA) is an optimization algorithm inspired by the natural foraging behavior of honey bees to find the optimal solution [24]. Figure. 2 shows the pseudo code for the algorithm in its simplest form. The algorithm requires a number of parameters to be set, namely: number of scout bees (n), number of sites selected out of n visited sites (m), number of best sites out of m selected sites (e), number of bees recruited for best e sites (nep), number of bees recruited for the other (m–e) selected sites (nsp), initial size of patches (ngh) which includes site and its neighborhood and stopping criterion.

1. Initialize the solution population.

2. Evaluate the fitness of the population.

3. While (stopping criterion is not met)

//Forming new population.

4. Select sites for neighborhood search.

5. Recruit bees for selected sites (more bees for the best e sites) and evaluate fitnesses.

6. Select the fittest bee from each site.

7. Assign remaining bees to search randomly and evaluate their fitnesses.

8. End While

Figure 2. Pseudo code of bees algorithm

The algorithm starts with the n scout bees being placed randomly in the search space. The fitness of the sites visited by the scout bees is evaluated in step 2. In step 4, bees that have the highest fitness are chosen as “selected bees” and sites visited by them are chosen for neighborhood search. Then, in steps 5 and 6, the algorithm conducts searches in the neighborhood of the selected sites, assigning more bees to search near to the best e sites.

The bees can be chosen directly according to the fitness associated with the sites they are visiting. Alternatively, the fitness values are used to determine the probability of the bees being selected. Searches in the neighborhood of the best e sites which represent more promising solutions are made more detailed by recruiting more bees to follow them than the other selected bees. The size of the flower patches $a = \{a_1, a_2, \dots, a_N\}$ is initially set to a large value, where N shows the number of variables. For each variable a_i, it is set as follows (Eq. (2)):

$$a_i = ngh(t) \times (max_i - min_i) \quad (2)$$

where t denotes the t^{th} iteration of the bees algorithm main loop. The size of a patch is kept unchanged as long as the local search procedure yields higher points of fitness. If the local search fails to bring any improvement in fitness, the size a is decreased. The updating of the neighborhood size follows the following heuristic formula which is defined using Eq. (3)

$$ngh(t+1) = 0.8 \times ngh(t) \quad (3)$$

Thus, following this strategy, the local search is initially defined over a large neighborhood, and has a largely explorative character. As the algorithm progresses, a more detailed search is needed to refine the current local optimum. Hence, the search is made increasingly exploitative, and the area around the optimum is searched more thoroughly. In step 6, for each patch only the bee with the highest fitness will be selected to form the next bee population.

In step 7, the remaining bees in the population are assigned randomly around the search space scouting for new potential solutions. These steps are repeated until a stopping criterion is met. At the end of each iteration, the colony will have two parts to its new population representatives from each selected patch and other scout bees assigned to conduct random searches. More details regarding to bees algorithm can be found in [24].

3. Proposed Method

The current procedure assumes that the image is recorded on an X‑ray film and that it is interpreted by a human expert. Obviously, this suffers from the human error and error with visual inspection, which may further be enhanced by poor quality of the images. This paper proposes an intelligent system based on combination of CNN and BA for dental caries diagnosis. The CNN has performed relatively well on image processing and pattern recognition. The proposed method includes two main modules: classifier module and optimization module. In the classifier module, CNN is used as the main classifier.

In the proposed method, the raw data is fed to CNN layer to extract new features. The features extracted from the convolution and pooling process were broken down into sequential components and fed to the fully connected layer for caries recognition. The caries are classified depending on the output of the fully connected layers. The effective extracted feature in the convolution layer makes the recognition task very easy for fully connected layer.

As mentioned, CNN has good performance in complicated pattern recognition problems, but there are many parameters and hyper-parameters that affect the network's performance significantly. The amount of unknown parameters will increase dramatically with the increase of hidden layer numbers and there are no systematic way to find the optimal value of these unknown parameters and hyper-parameters. To overcome this problem, we have proposed an intelligent method based on BA to find the optimal architecture of the CNN. The main structure of the proposed method is shown in Figure 3.

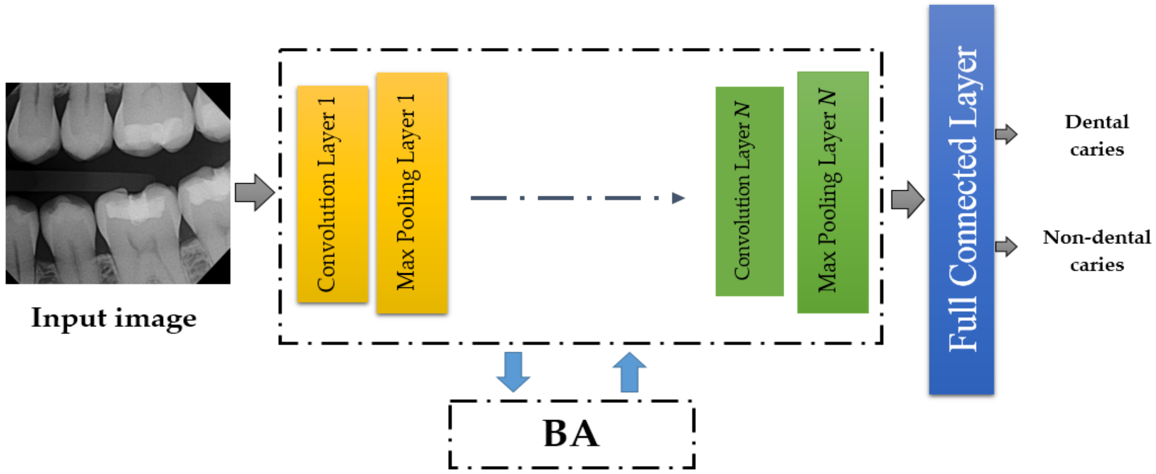

Figure 3. The main structure of the proposed system

One of the key issues in evaluating the performance of a classification approach is the capability of correct classification of new examples. The classification performance of two class problems can be interpreted in a confusion matrix as shown in Table 1.

Table 1. Confusion matrix

Data class	Classified as positive	Classified as negative
Positive	TP	FN
Negative	FP	TN

The entries in the confusion matrix have the following meaning in the context of our study:

TP is the number of correct predictions that an instance is positive.

FN is the number of incorrect predictions that an instance is negative,

FP is the number of incorrect predictions that an instance positive

TN is the number of correct predictions that an instance is negative.

The most commonly used measure to evaluate the performance of a classifier is recognition accuracy (RA) rate. The RA is the proportion of the total number of predictions that were correct to all samples. It is determined using the Eq. (4)

$$RA = \frac{TP + TN}{TP + FN + FP + TN} \times 100 \qquad (4)$$

4. Simulation Result

In this section the performance of the proposed method is investigated. The computational experiments for this section were done on Intel core i7 with 32 GB RAM using ASUS computer. In this study, 40% of data were used in order for training the classifiers and the rest for testing.

4.1. Dataset

In this study, the Anonymized periapical radiographic image dataset acquired between March 2017 and October 2018 in the dentistry department of Shahid Beheshti University is used for evaluating the performance of proposed method. All images were clearly revalidated, and dental caries, including enamel and dentinal carious lesions (excluding deciduous teeth), were distinguished from non-dental caries by four calibrated board-certified dentists. The dataset excluded all periapical radiographic images in which the diagnosis of the four examiners did not match, and included the periapical radiographic images for which all four examiners agreed to the diagnosis of dental caries.

The dataset consisted of a total of 3000 periapical radiographic images of 778 (25.9%) maxillary premolars, 769 (25.6%) maximally molars, 722 (24.1%) mandibular premolars, and 731 (24.4%) mandibular molars. There were 781 (23.9%) premolars and 772 (25.7%) molars that were diagnosed as dental caries, and 719 (26.1%) premolars and 728 (24.3%) molars diagnosed as non-dental caries. Periapical radiograph images diagnosed as dental caries and non-dental caries were cropped to show only one tooth per image and optimal position. Images were calibrated to standardize contrast between gray/white matter and lesions.

4.2. Performance of the Conventional CNN

In this experiment, the effect of parameters and hyperparameters on CNN performance is investigated. For this purpose, several CNNs with different architecture have been built and the obtained results are listed in Table 2. It can be seen that the CNN with three hidden layer and Max Pooling functions in POOL layer has the best recognition accuracy. Based on Table 2 we can conclude that the architecture of CNN has high effect on its accuracy and its robustness. The value of standard deviation (SD) for different architectures are listed in the table. In order to indicate the details of the recognition for each pattern, the confusion matrix of recognizer is shown by Table 3.

Table 2. Evaluation of CNN with different architecures

NHL	a	TPL	Hyper-parameters	RA (%)	SD
1	0.01	Max	$K_{1C} = 10, F_{1C} = 4, S_{1C} = 1, P_{1C} = 1, F_{1P} = 5, S_{1C} = 1$	88.75	± 1.19
1	0.005	Max	$K_{1C} = 10, F_{1C} = 4, S_{1C} = 1, P_{1C} = 1, F_{1P} = 5, S_{1C} = 1$	91.25	± 1.14
2	0.005	Max	$K_{1C} = 10, F_{1C} = 4, S_{1C} = 1, P_{1C} = 1, F_{1P} = 5, S_{1C} = 1$ $K_{2C} = 12, F_{2C} = 3, S_{2C} = 1, P_{2C} = 1, F_{2P} = 3, S_{2C} = 1$	96.31	± 0.81
2	0.005	Average	$K_{1C} = 10, F_{1C} = 4, S_{1C} = 1, P_{1C} = 1, F_{1P} = 5, S_{1C} = 1$ $K_{2C} = 14, F_{2C} = 3, S_{2C} = 1, P_{2C} = 2, F_{2P} = 2, S_{2C} = 1$	96.18	± 0.87
3	0.005	Max	$K_{1C} = 10, F_{1C} = 4, S_{1C} = 1, P_{1C} = 1, F_{1P} = 5, S_{1C} = 1$ $K_{2C} = 12, F_{2C} = 3, S_{2C} = 1, P_{2C} = 1, F_{2P} = 3, S_{2C} = 1$ $K_{3C} = 18, F_{3C} = 3, S_{3C} = 1, P_{3C} = 1, F_{3P} = 3, S_{3C} = 1$	97.18	± 0.49
3	0.005	L2-norm	$K_{1C} = 10, F_{1C} = 4, S_{1C} = 1, P_{1C} = 1, F_{1P} = 5, S_{1C} = 1$ $K_{2C} = 14, F_{2C} = 3, S_{2C} = 2, P_{2C} = 2, F_{2P} = 2, S_{2C} = 1$ $K_{3C} = 24, F_{3C} = 3, S_{3C} = 1, P_{3C} = 1, F_{3P} = 3, S_{3C} = 1$	96.87	± 0.53

Table 3. Confusion matrix of conventional CNN for the best obtained result (97.18%)

	Dental caries	Non-dental caries
Dental caries	828	22
Non-dental caries	29	921

4.3. Performance of the proposed method

In this experiment, the performance of the proposed method has been investigated. Deep learning architecture is represented by parameterized functions and hence the optimal parameters have direct impact on its accuracy. In order to find out the optimal values of these parameters and hyper-parameters, we used BA as the optimization algorithm. The BA should find the best parameters and hyper-parameters of the CNN to enhance the RA rate. Table 4 shows the BA control parameters.

Table 4. BA control parameters

Number of scout bees (n)	30
Number of sites selected for neighborhood search, (m)	5
Number of best “elite” sites out of m selected sites, (e)	3
Number of bees recruited for best e sites, (nep)	3
Number of bees recruited for the other (m–e) selected sites, (nsp)	3
Number of iterations (R)	100

The obtained results using the proposed method are listed in Table 5. Based on BA, the CNN with five hidden layer, learning rate 0.0037 and Max Pooling function in POOL layer has the best recognition accuracy, 99.38%. The confusion matrix of the proposed method is shown by Table 6. It can be seen that the correct RA rate has increased significantly. The SD of the proposed method is zero (SD = ± 0.0) which indactes its robustness.

4.4. Comparison with Different Classifiers

In this experiment, the performance of the proposed method has been compared with other classifiers. In this respect, probabilistic neural networks (PNN), Multi layered Perceptron (MLP) neural network with different training algorithm such as Back propagation (BP) learning algorithm, Resilient propagation (RP) learning algorithm and Levenberg Marquardt (LM), Radial Basis Function Neural Network (RBFNN), Adaptive Neuro-Fuzzy Inference System (ANFIS) are considered. In this experiment, we used raw data as the input of the classifiers. It can be seen from Table 7 that the proposed method (BA-CNN) has much better performance in comparison with other methods. Also the proposed method has robust performance.

Table 5. Performance of the proposed method and the proposed architecture

Layer	No. Filters (K)	Filter Size (F)	Stride (S)	Zero padding (P)
0	-	-	-	-
1st CONV	16	24 × 24	1	1
1st POOL	16	16 × 16	2	-
2nd CONV	28	20 × 20	1	1
2nd POOL	28	11 × 11	2	-
3rd CONV	60	16 × 16	1	2
3rd POOL	60	8 × 8	2	-
4th CONV	112	6 × 6	1	1
4th POOL	112	3 × 3	1	-
5th CONV	158	4 × 4	1	1
5th POOL	158	2 × 2	1	-

Table 6. Confusion matrix of the proposed method

	Dental caries	Non-dental caries
Dental caries	846	4
Non-dental caries	7	943

Table 7. Comparison the performance of proposed classifier with other classifiers using raw data

Classifier	RA (%)	SD
PNN	93.26	± 2.16
MLP (BP)	91.43	± 3.70
MLP (RP)	95.24	± 1.43
MLP (LM)	96.17	± 1.28
RBFNN	96.62	± 1.21
ANFIS	96.81	± 0.78
Proposed method	99.38	± 0.0

5. Conclusion

Accurate detection and diagnosis of dental caries reduces the cost of oral health management, and increases the likelihood of natural tooth preservation in the long term. In this study a new method based on intelligent combination of

CCN and BA proposed for automatic diagnosis of dental caries. Several experiments were performed to evaluate the performance of the proposed method and the obtained results showed that the proposed method has better performance in comparison with other methods. The proposed hybrid system of CNN and BA model has delivered promising results as compared to the other conventional studies. In the proposed method, feature extraction and selection techniques are not required.

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